Expression-Invariant Face Recognition via 3D Face Reconstruction Using Gabor Filter Bank from a 2D Single Image

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***Abstract*— In this paper, a novel method for expression-insensitive face recognition is proposed from only a 2D single image in a gallery including any facial expressions. A 3D Generic Elastic Model (3D GEM) is used to reconstruct a 3D model of each human face in the present database using only a single 2D frontal image with/without facial expressions. Then, the rigid parts of the face are extracted from both the texture and reconstructed depth based on 2D facial land-marks. Afterwards, the Gabor filter bank was applied to the extracted rigid-part of the face to extract the feature vectors from both texture and reconstructed depth images. Finally, by combining 2D and 3D feature vectors, the final feature vectors are generated and classified by the Support Vector Machine (SVM). Favorable outcomes were acquired to handle expression changes on the available image database based on the proposed method compared to several state-of-the-arts in expression-insensitive face recognition.**

Keywords—Face recognition; 3D shape recovery; Gesture and Behavior Analysis.

I. Introduction

Expression-insensitive face recognition is one of the most difficult and challenging tasks in computer vision because of the changes in expression of human faces. However, few are focused on how to robustly recognize faces with expressions under the restriction of one 2D single training sample for each class. Available expression-insensitive face recognition methods can be mostly categorized into two separate types: 1) 2D-based techniques which use the 2D image to handle the expression in face recognition [1, 2] and 2) 3D-based methods which employ a 3D model (including depth and texture images) to handle expression in face recognition faces [3, 4, 5].

2D-based methods which are used from only a single image in the training set can be roughly divided into two main categories: model-based and optical flow-based. The basic idea in the model-based category is to warp images to similar global face transforms as the ones used for training. The concept of separately modeling texture and transform information has been applied in the Active Shape Model (ASM) and Active Appearance Model (AAM) [6, 7], and etc. Face transform is defined via a set of feature points in ASM, while face texture can be warped to the mean shape in AAM. Ramachandran et al. [8] presented preprocessing steps to convert a smiling face to a neutral face. Li et al. [9] applied a face mask for face transform normalization, and then calculated the Eigenspaces for transform and texture separately. However, this approach but not all images can be well warped to a neutral image because of the lack of texture in certain regions, like the openness of the mouth.

The second category of 2D methods to handle expression in face recognition is optical flow which computes the face warping conversion. Optical flow has been used in the task of expression recognition [10, 11]. However, it is difficult to study the local motion in the feature space to find out the expression change for each face, since diverse persons have expressions in diverse motion styles. Martinez [12] proposed a weighting technique that independently weighs the local areas which are less sensitive to expressional changes. The intensity alternations due to expression may misinform the calculation of optical flow. Hsieh et al. [1] also presented an incorporated face recognition system that is robust against facial expressions by combining information from the calculated inside optical flow and the synthesized face image in a probabilistic framework.

Recently, Heo and Savvides [13] proposed generic elastic models (GEMs) as a novel impressive, fast and trustworthy 3D reconstruction technique from a single 2D image. In fact, this method planned a 3D face model that could be efficiently produced by using generic depth models that could be elastically deformed to align with facial landmarks. Also, Heo and Savvides [2] proposed gender and ethnicity specific GEMs (GE-GEMs) in order to synthesize new 2D face images at optional poses using gender and ethnicity specific models with a more perfect and better quality than the GEM approach. In this method, it was also assumed that the depth data of faces was significantly less different among the same gender and ethnicity groups. In the GE-GEMs and GEMs approaches, precise 3D models could be created using only a single image at a comparatively fewer computational cost compared to the former methods. Moreover, Heo and Savvides [2] employed the GEM and GE-GEM models in the face recognition system for handling the face pose. However, in this method, a 2D warping and 3D warping method was proposed to handle expression in face recognition. Also, another extending of GEM methods that is expression-invariant can be found in [30-35].

1051-4651/14 $31.00 © 2014 IEEE
DOI 10.1109/ICPR.2014.805

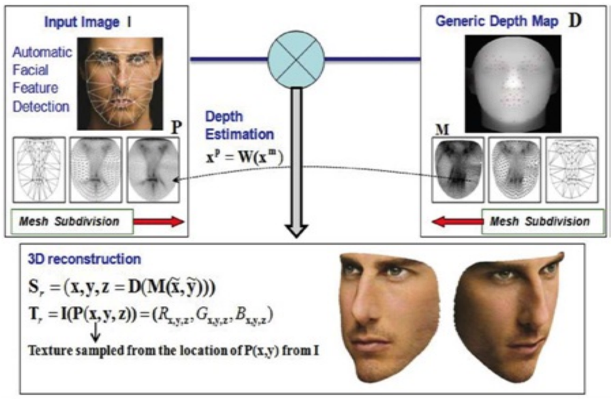

Fig. 1. GEM method for 3D face reconstruction from a single frontal image. [13]

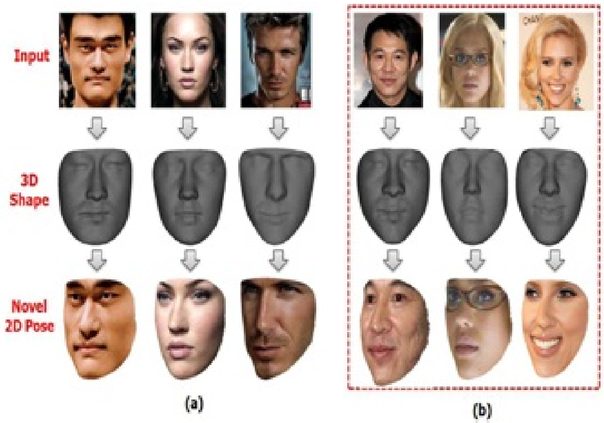

Fig. 2. Examples of GEM-based 3D modeling from 2D images: (a) accurate 3D reconstructions and (b) inaccurate 3D reconstructions with undesirable artifacts. [15]

In this paper, a new combined approach is proposed from 3D-based and 2D-based methods. Accordingly, a 3D model was initially reconstructed from training 2D frontal face images with arbitrary facial expression. To reconstruct a 3D model from each human frontal face with arbitrary facial expression, a Generic Elastic Model (GEM) is used. Then, the rigid parts of the face were extracted from both texture and reconstructed depth based on 2D facial landmarks. Afterwards, the Gabor filter bank was applied to the extracted rigid-part to extract the feature vectors from both texture and reconstructed depth images. Finally, by combining 2D and 3D feature vectors, the final feature vectors are generated and classified by the Support Vector Machine (SVM).

This paper is organized as follows: Section 2 describes the 3D face modeling method from a single frontal face image. In section 3, the feature extraction manner of the Gabor filter banks are proposed for expression-insensitive face recognition. Experimental evaluations are given in section 4 and conclusions are presented in section 5.

II. 3D Face Reconstruction by GEM

In this section, the GEM framework is described for 3D face reconstruction from a single frontal image. Recently, Heo and Savvides [13] proposed Generic Elastic Models (GEMs) as a novel impressive, fast and trustworthy 3D reconstruction technique from a single 2D image. In fact, this method planned a 3D face model that could be efficiently produced by using generic depth models that could be elastically deformed to align with facial landmarks. The general technique of the original GEM method is displayed in Fig. 1. The face was initially detected by facial landmarks. Then, each face (I) is divided into a mesh of triangular polygons (P). Correspondingly, the generic depth-model (D) of the face is divided to a mesh (M) from facial landmark points. When facial landmarks are extracted between input face images and the generic depth-model, the density of meshes M and P concurrently increase utilizing loop subdivision [14]. The subdivision method utilized in the GEM method can be considered a middle stage for creating dense correspondence between the input mesh of face and mesh of the depth model.

A piecewise affine conversion (W) is employed for warping the GEM depth map (D) sampled in face landmarks of M onto input triangle mesh (P) in order to approximate depth data. Each pixel in the input face image has an exact corresponding pixel in the depth model and intensity of the depth model can be utilized for estimating depth in the input face image. Finally, the reconstructed 3D model can be interpolated using intensity of the input image I(P(x, y)) experimented in 2D face landmarks of P(x, y).

Therefore, 3D face reconstruction by the GEM method is expressed by:

$$S_r = (x, y, z = D(M(\tilde{x}, \tilde{y}))),$$
$$\mathrm{T_r} = I(P(x, y, z)) = (R_{x,y,z}, G_{x,y,z}, B_{x,y,z}) \tag{1}$$

where $\tilde{x}$ and $\tilde{y}$ in M are registered pixels x and y in image P. As mentioned, the main drawback of this method is the problem of 3D face reconstruction from images with a variety of facial expressions.

To show the efficiency of GEM in a qualitative manner, the reconstructed 3D models are shown in Fig. 2, each obtained from a single downloaded image from the Internet. The second row images include the reconstructed 3D models, the third row images illustrate the textured 3D faces, and the bottom row shows novel views of one of the 3D models. These 3D models are generated from the corresponding input images in the first row, respectively. As evidenced by these 3D models, the reconstructed 3D models are all different, especially around the nose area. The one limitation of the approach is that severe textural are saw artifacts when attempting to generate 3D models from images with eyeglasses since the GEM do not model or remove them, and consequently the texture of the eyeglasses get plastered onto the face model (see Fig. 2b). Also, the values of depth (z) are not considered for modeling the facial expression and only spatial location in x and y directions are changed (see Fig. 2b). Since the impacts of facial expression and occlusion are not important for purpose of expression-invariant face recognition, the GEM method can help to counteract these impacts. In fact, the GEM method is masked the expression changing in z

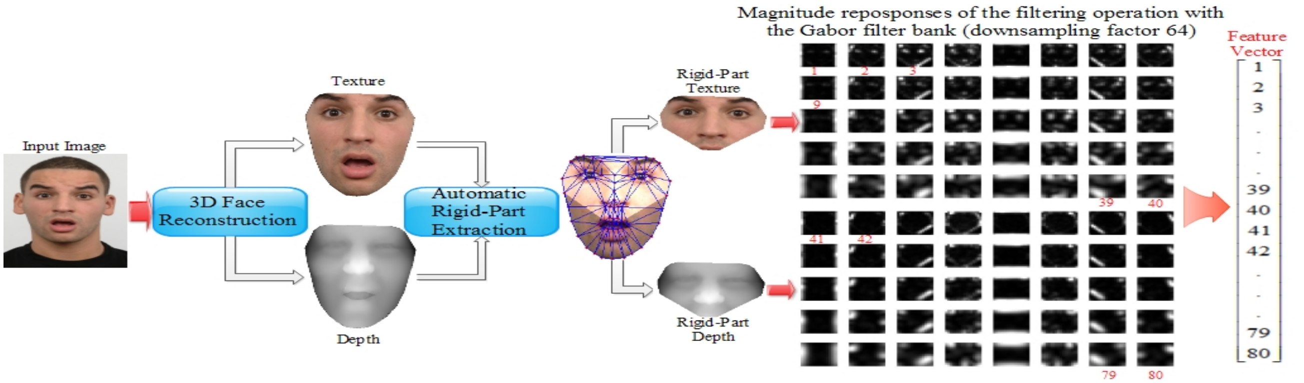

Fig. 3. Visual illustration of feature extraction by the Gabor filter bank from arbitrary frontal face images.

direction and occlusion in 3D face modeling that is effective for purpose of expression-invariant face recognition. As it is evidence from Fig. 2 the images that have facial expression in addition to that it is different in texture image, in terms of facial depth are discriminative especially in regions of eyes and nose. Thus, the facial depth is discriminative for gender classification and is added to texture images for feature extraction.

III. Expression-Insensitive Face Recognition

In this section, the feature extraction method is proposed from 2D images by the Gabor filter bank [16] based on 3D face reconstruction for expression-insensitive face recognition. Then, the method for expression-insensitive face recognition is represented.

A. Feature Extraction by the Gabor Filter Bank

Visual illustration of the proposed method for extracting the feature by the Gabor filter bank [16] for expression-insensitive face recognition is shown in Fig. 3. Based on the proposed method, the process can be summarized as follows:

1- Input: a 2D face image.
2- For each input face image, the 3D face was reconstructed and texture and depth images were extracted from reconstructed models.
3- The rigid-parts of the face were extracted from both depth and texture images based on location of facial landmarks that are shown in Fig. 3. The rigid-parts of the face have the least variation in the face against facial expression. In this work, the Constrained Local Model (CLM) [17-21] was applied for automatically extracting input face landmarks which were robust by the facial expression face.
4- The feature vectors were extracted based on Fig. 3 (example of feature extraction for each image as demonstrated in Fig. 3) from each of the depth and texture images by the Gabor filter bank. Finally, the feature vector was created from the entire features based on Fig. 3.
5- Output: feature vector.

To extract the Gabor feature based on Fig. 3, a Gabor filter bank with a size of 40 (5*8 with 8 directions and 5 magnitudes) was applied to each image. Then, a feature vector was created from the entire 40 magnitude of the 40 Gabor filter bank which was low dimensional by the down sampling method.

B. Face Recognition System

Visual illustration of the expression-insensitive face recognition system proposed in this paper is shown in Fig. 4. The proposed system operated in two offline and online stages. In the offline stage, feature vectors were extracted from a single frontal face image of each person in specific facial expression based on Fig. 3. Then, a dictionary of feature vectors was generated for the training process. In the online stage, similarity, feature vectors were extracted from test images based on Fig. 3. Finally, face recognition was performed by the Support Vector Machine (SVM) [22] (linear) between the dictionary of feature vectors and feature vector of the test image.

IV. Experiments

In this experiment a subset of the Radboud database with seven different facial expressions were used for testing images. The Radboud faces database [23] included 20 Caucasian male adults, 19 Caucasian female adults, 18 Moroccan male adults, 6 Caucasian female children and 4 Caucasian male children and face images of each person were captured with seven different expressions in five different poses. The seven expressions included are neutral, sad, angry,

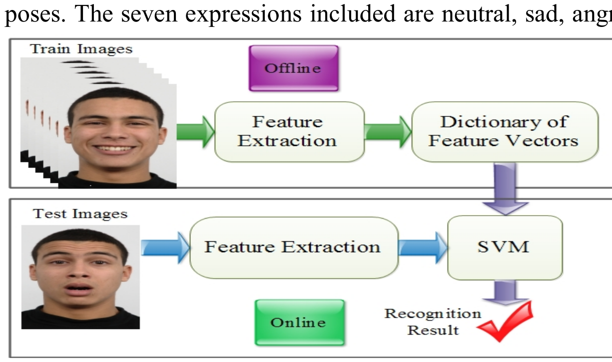

Fig. 4. Visual illustration of the expression-invariant face recognition from a single face image.

Fig. 5. Sample of the face images utilized for the present experiments with seven facial expressions.

fearful, disgusted, happy and surprised. In this part of the work, a subset of 57 subjects were utilized which included 20 Caucasian males, 19 Caucasian females and 18 Moroccan males in seven facial expressions. Examples of seven facial expressions in the Radboud faces database are shown in Fig. 5.

To evaluate the proposed method, training and testing images were categorized based on the type of facial expressions. Accordingly, images with one type of facial expressions were used as the training images and the other images were used as testing images. The results of the proposed method for expression-insensitive face recognition based on the type of facial expression in the target image are shown in Table I. As shown in Table I, the proposed method for expression-insensitive face recognition has high performance in the identification rate to handle the expression changes.

Moreover, to further evaluate the accuracy of the present method for handling expression in face recognition from only a single image in the gallery, the obtained results were compared with six 2D and 3D methods for tests:

1- The 2D Warping [2] (2DW) method which included the model-based method to handle the expression in face recognition. In this method, after warping the target image for expression of the training image, face recognition was performed by cosine distance similarity based on the proposed method in [2].
2- The 2D Warping+ Gabor filter bank (2DW+G) which included model-based approaches. In this case, instead of using cosine distance similarity, a Gabor filter bank method was applied after 2D warping to extract the features for performing face recognition.
3- The 3D Warping [2] + GEM method [13] (3DW+GEM) which included a compound of model-based and 3D-based methods to handle the expression in face recognition. In this method, 3D face was initially reconstructed by the GEM method. Then, after 3D warping, the target image for expression of the training image, face recognition was performed by cosine distance similarity based on the proposed

TABLE I. PERFORMANCE OF THE PROPOSED METHOOD IN IDENTIFICATION RATE (PERCENTAGE) UNDER DIFFERENT EXPRESSION IN TESTING AND ONE EXPRESSIONS IN TRAINING IMAGES FROM THE RADBOUD DATABASE.

Train\Test	**Neutral**	**Happy**	**Disgusted**	**Fearful**	**Surprised**	**Angry**	**Sad**	**Mean**
Neutral	100	93.1	95.4	97.6	90.3	96.8	98.5	**95.9**
Happy	90.5	97.3	94.5	91.8	87.3	91.8	93.2	**92.3**
Disgusted	97.2	90.6	92.1	91.0	87.4	98.3	94.2	**92.9**
Fearful	93.5	87.2	93.6	100	87.3	90.3	91.8	**91.9**
Surprised	93.4	91.8	94.4	96.4	92.4	96.4	90.7	**93.6**
Angry	93.2	92.3	100	93.2	92.4	100	92.2	**94.7**
Sad	100	91.7	93.8	97.3	92.1	95.4	99.3	**95.6**

TABLE II. EVALUATING MEAN RANK-1 IDENTIFICATION RATE (PERCENTAGE) UNDER DIFFERENT EXPRESSIONS IN TESTING IMAGES BASED ON TYPE OF EXPRESSION IN TRAINING IMAGES FROM THE RADBOUD DATABASE.

Methods\Train	**Neutral**	**Happy**	**Disgusted**	**Fearful**	**Surprised**	**Angry**	**Sad**	**Overall**
2DW	78.8	73.0	77.5	74.2	71.7	76.8	76.9	75.5
2DW+G	83.0	80.2	83.4	80.5	77.3	82.4	83.1	81.4
3DW+GEM	88.5	83.5	85.4	84.1	81.4	87.2	86.8	85.2
3DW+GEM+G	89.3	83.1	87.8	84.0	80.9	88.6	86.3	85.7
Proposed method	**95.9**	**92.3**	**92.9**	**91.9**	**93.6**	**94.7**	**95.6**	**93.8**

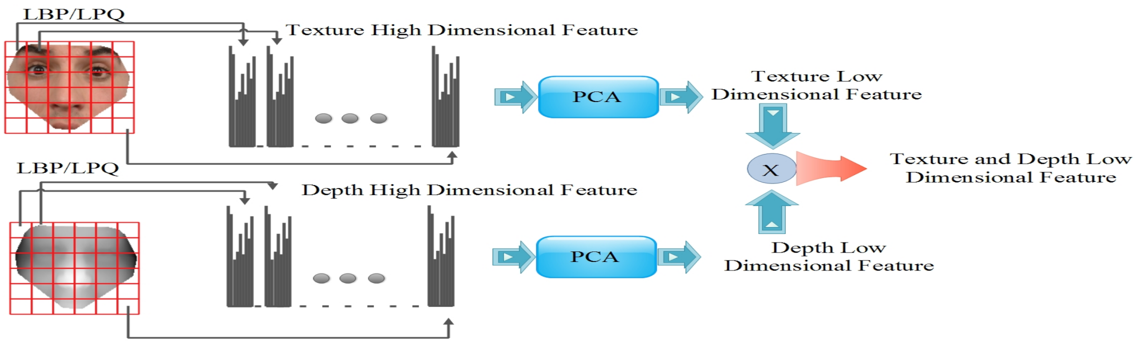

Fig. 6. Visual illustration of feature extraction by LBP/LPQ from rigid part of face images using Principal Component Analysis (PCA).

method in [2].

4- The 3D Warping + GEM + Gabor filter bank (3DW+GEM+G) method which included a compound of model-based and 3D-based methods to handle the expression in face recognition. In this case, instead of using cosine distance similarity, a Gabor filter bank method was applied after 3D warping to extract the features for performing face recognition.

The proposed expression-insensitive face recognition method seems to outperform the other implemented approaches. These measurement results are shown in Table II. Table II shows the mean identification rate in 399 (57*7 which 57 number of subject and 7 facial expression per subject) testing face images based on the type of facial expression in training images. As it is obvious from the results, performance of the present method for expression-insensitive face recognition was improved, especially in facial expressions with most variation in expressions. The proposed method performed better than other methods for expression-insensitive face recognition.

To further evaluate the impact of 3D reconstruction in feature extraction, the LBP and LPQ feature extraction method was compared with the utilized Gabor filter bank. Hence, the LBP and LPQ feature vectors were extracted from the rigid part of the face based on Fig.6. Therefore, five methods were compared with the proposed method:

1- Local Binary Pattern (LBP) [24] method. In this method, the LBP operator was applied to only the texture image in the rigid part of the face for feature extraction based on Fig. 6.

2- LBP+GEM method. In this method, the LBP operator was applied to both texture and depth images in the rigid part of the face which are reconstructed by the GEM method instead of applying it to texture. Then, the feature vector was created by combining the extracted features on both texture and depth images based on Fig. 6.

3- Local phase quantization (LPQ) [25] method. In this method, the LPQ operator was applied to only the texture image in the rigid part of the face for feature extraction based on Fig. 6.

4- LPQ+GEM method. In this method, the LPQ operator was applied to both texture and depth images in the rigid part of the face instead of applying it to texture. Then, the feature vector was created by combining the extracted features of both texture and depth images based on Fig. 6.

5- Gabor filters bank method. In this method, feature vectors were created by applying the Gabor filter bank to only the texture image in the rigid part of the face and based on Fig. 3.

The results of this evaluation are given in Table III. As it is obvious from the results, performance of the present method for expression-insensitive face recognition was improved rather than methods that used only texture images to extract the features. Thus, the reconstructed depth from a single frontal image is effective in feature extraction based on the proposed method. Also, in another category of comparison,

TABLE III. EVALUATING OVERALL MEAN RANK-1 IDENTIFICATION RATE (PERCENTAGE) UNDER DIFFERENT FEATURE EXTRACTION IN PROPOSED METHOD FROM THE RADBOUD DATABASE.

Methods	Recognition Rate (%)
LBP [24]	83.3
LBP+GEM	**91.6**
LPQ [25]	82.7
LPQ+GEM	**90.1**
Gabor [16]	80.8
Proposed method	**93.8**

TABLE IV EVALUATING OVERALL MEAN RANK-1 IDENTIFICATION RATE (PERCENTAGE) IN COMPARISON WITH STATE-OF-THE-ART METHOD FROM THE RADBOUD DATABASE.

Methods	Recognition Rate (%)
LDA [29]	65.8
ICA [28]	68.2
PCA [26]	72.9
Eigenface [27]	75.6
Fisherface [27]	76.0
Proposed method	**93.8**

several popular state-of-the-art methods which were discussed in the introduction section were compared with the proposed method. The results of this comparison with the state-of-the-art methods are given in Table IV.

V. CONCLUSION

In this paper, a new combined approach was proposed from 3D-based and 2D-based methods for expression-insensitive face recognition from only a single 2D frontal image with arbitrary expression in the gallery and facial expression change in target images. The proposed method was tested on available image databases in order to perform expression-insensitive face recognition. Also, the obtained results showed which one could handle the facial expression based proposed method to perform expression insensitive face recognition. It was demonstrated that performance of the proposed method for face recognition was better than similar approaches and experimental results of the proposed method were compared with classical, as well as state-of-the-art methods.

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